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Session 6 - Environmental Systems: Management and Optimisation

Session 7 - New Methods and Technologies for Medicine and Biology

Session 8 - Embedded System Design and Application

Session 9 - Image Processing, Image Analysis and Computer Vision

Session 10 - Mobile Communications

Session 11 - Education in Computer Science and Automation

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Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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Demand Forecasting of Water Usage based on Kalman Filtering

ABSTRACT

In this work a method of demand forecasting of water usage which is based on Kalman filtering is presented. The Kalman filter is a method that provides an efficient computational solution in least square sense. It has thus received much attention for estimation purposes. To demonstrate the efficiency of the proposed technique, it is used to predict the water usage demand of Beijing. The data employed in the forecasting process are the previously forecasted demand and several exogenous influences. This method employs a simple mathematical process with less computational consumption.

INTRODUCTION

Signal modeling is an attractive topic and plays an important role in many fields such as analyzing stock market, forecasting water level in dams, forecasting car sales volume, weather forecasting or even in water usage demand. In many applications, it is preferable to select the model parameters so as to minimize a sum of squared error criterion. This technique often leads to satisfactory results and has a closed form solution to the interested problem. Therefore, least squared error (LSE) modeling has been widely used in various of data analysis problems. Kalman filtering is one of well-known techniques, which is based on least squared error minimization. Basically, Kalman filtering behaves as a tool to analyze and solve the problem of estimation that has either one or more unknown variables at a time. It can be applied for filtering problem, smoothing and also for prediction [3]. Therefore, it is widely applied in many fields [5,6,11,14]. In [8], forecasting of structural time series models and the Kalman filter were described. It is thus initiating the idea to apply the concept of the Kalman filtering for forecasting in water usage demand in this work.

The process of forecasting using this method is much simpler than those approaches [1,4]. In addition, the computational consumption of this method is quite less. The concept of the proposed technique will be given in section of “basic principles”. Later, the forecasting results of water demand using the proposed approach compared with linear regression model will be given in section “simulation results”. Finally, some conclusions will be drawn.

BASIC PRINCIPLES

Multiple linear regression

In this work, a multiple linear regression model is selected to be a method of statistical analysis. Let W_k be a predicted water usage demand of k^{th} year in which a multiple linear regression model can be expressed as

$$W_k = \alpha + \beta\, H_{k\text{-}1} + \gamma\, W_{k\text{-}1} + \varphi\, E_{k\text{-}1} + \phi\, P_{k\text{-}1} \tag{1}$$

where α, β, γ, φ and ϕ are modeling parameters, W_k is the actual water demand, H_{k-1} is the previous number of households in the k^{th} year, W_{k-1} is the previous water demand, E_{k-1} is the previous number of employment and $P_{k\text{-}1}$ is the previous water price. Based on the concept of signal estimation, the modeling parameters are selected, so that least squared error is minimized (equation 2). Due to the fact that there could be some effects that are correlated to some explanatory variables the ordinary least mean squares method (OLS) is biased and inconsistent. Therefore, in this paper, the weighted least mean squares method is used, so that points with a greater weight contribute more to the fit.

$$\min \sum_{i=1}^{n} w_i \left(\hat{Y}_i \text{ - } Y_i\right)^2 \tag{2}$$

In matrix notation, the weighted least squares estimator of $\hat{\Theta}$ (vector of all parameters) is

$$\hat{\Theta} = \left(X^T\, W X\right)^{\text{-}1} X^T\, W\, Y \tag{3}$$

w_i is given as the inverse of the variance, giving points with a lower variance a greater statistical weight:

$$w_i = \frac{1}{\sigma_i^2} \tag{4}$$

and

$$W = diag\left\{w_1,\ \ldots,\ w_n\right\} \tag{5}$$

The parameters in (1) were estimated for the regression model based on the data from 1996 to 2002 found at [2,10]. Their standard deviations were also calculated (table 1).

Parameter	α	β	γ	φ	ϕ
Best Estimate	1.2799	-8.95E-04	-6.874E-4	-0.2142	0.0038
σ	0.7511	0.0019	9.71E-04	0.486	0.0016

Table 1: Statistical measures for the estimate parameters

Proposed Kalman filtering technique

In 1960, Kalman published his well-known paper [9] describing a recursive solution to the discrete-data linear filtering problem. Since then, due in large part to advances in digital computing; the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous navigation. A good overview on an introduction to the Kalman filter can be found [12]. Here the Kalman filtering concept will be briefly given as follows. In the Kalman filtering concept, the general problem of estimating the state $x \in \Re^n$ of a discrete-time controlled process is described by the following equation

$$x_k = A\, x_{k-1} + B\, u_k + w_{k-1} \qquad (6)$$

where A is transition matrix of prediction system, B is matrix of optional control input, u_k and w_k represent the state input and process noise, respectively.

In addition, a measurement $z \in \Re^m$ of the state is

$$z_k = H\, x_k + v_k \qquad (7)$$

where H is transition matrix of measurement system and v_k is measurement noise.

By employing a form of feedback control, the Kalman filter estimates the process state at some time and then obtains feedback in the form of measurements. With this in mind, the Kalman filtering equations are classified into to groups

- time update (prediction)
- measurement update (correction)

For describing the time series a simple AR(1) model is used. The general description for the AR model is shown in equation (13). This equation will be adapted to the AR state space model (equations (6), (7)) [7,13]. The parameters a_i excluding a_1 are set to zero.

$$\mathrm{y_k = a_1\, y_{k-1} + a_2\, y_{k-2} + \ldots + a_n\, y_{k-n}} \qquad (13)$$

The described method was implemented by using Matlab.

Additionally, the Kalman filtering technique is applied with regression method mentioned in previous subsection. The regression method is used for estimation of the a_1 of the AR(1) model. It is also used for parameter estimation of the ARX model (AR model with external influences) described in the previous subsection (equation 1). The general ARX model description is shown in equation 16.

$$y_k = a_1 y_{k\text{-}1} + a_2 y_{k\text{-}2} + \ldots + a_n\, y_{k\text{-}n} + b_{1,1} u_{1,\,k} + \ldots + b_{1,\,m} u_{1,\,k\text{-}m\text{-}1} + b_{2,1} u_{2,\,k} + \ldots + b_{2,\,p} u_{1,\,k\text{-}p\text{-}1} + \ldots \tag{16}$$

Basically, by using ARX model, the number of households, employment and water price in each year is required in the prediction process. In summary, there are four approaches to be compared in this paper:

- Regression based ARX model (model 1),
- Kalman filtering technique using AR(1) model with $a_1 = 1$ (model 2),
- Kalman filtering technique using AR(1) model with previous identified a_1 parameter by regression (model 3) and
- Regression based ARX model with additional use of the Kalman filter (model 4).

The four concepts are implemented in Matlab, which the results are illustrated in the following section.

SELECTION OF MEASUREMENT NOISES

Long term measurement noise strength can be approximated by looking at a short time period of the time series curve. If we assume that we would approximate it by a dynamic linear model, we can approximate the standard derivation of the model measurements noise by looking at the strength of residuals. The selected variance of noise was $\sigma_x^2 = 0.001$, which quite well fits to the observed residuals.

The choice of measurement noises in long term models can be done, for example, by visual inspection, because the exact choice of noise strength is not crucial. The process noise strength is selected based on cross validation, which implicitly corrects also the choice of measurement noise strength. By visual inspection a suitable measurement noise for the AR-estimation model was $\sigma_{ar}^2 = 0{,}1$. Because we are interested in the missing parts of data in prediction with Kalman filter based model. The best way to do this is to follow the measurements exactly whenever there are measurements and use AR models for prediction only when there are no measurements.

This happens when the measurement noise level is set to as low as possible and the process noise is set to a moderate value. Our choice for the noise level in the Kalman filter model was $\sigma_p^2 = 0.01$.

SIMULATION RESULTS

Raw data (water demand, population, gross domestic product) from 1996 to 2002 are employed in the forecasting process [2,10]. The data from 1997 to 2003 were employed to examine the prediction efficiency of the three techniques. The results are shown in figure 1. It can be seen that the methods using the ARX model outperforms the other two methods and the Kalman filter provides also advantages to the simple regression based ARX model.

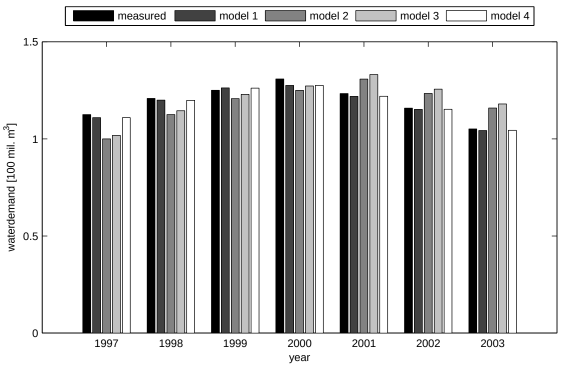

Figure 1: Water demand forecasting.

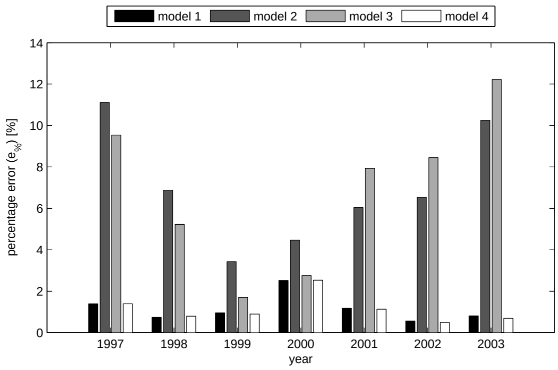

Figure 2: Percentage forecasting errors

The comparison of the forecasting error among these are shown in Figure 7 and also in Table 7, where the amount of error is calculated by

$$e_{\%} = \left(\frac{\left| D_k - \hat{D}_k \right|}{D_k} \right) \cdot 100\% \tag{10}$$

where $e_{\%}$ is the percentage error, D_k the actual water demand and $\hat{D}_k$ the forecasted water demand.

Year	1997	1998	1999	2000	2001	2002	2003
Model 1	1.39	0.74	0.96	2.52	1.17	0.56	0.81
Model 2	11.11	6.88	3.43	4.47	6.04	6.54	10.25
Model 3	9.54	5.23	1.69	2.76	7.93	8.45	12.23
Model 4	1.39	0.79	0.89	2.53	1.13	0.49	0.69

Table 2: Table of the forecasting errors of the different methods

CONCLUSIONS

This paper introduced a technique based on Kalman filtering, for forecasting water usage demand.

Based on the raw data from year 1997 to 2003, the forecasting results of using regression technique and the proposed approach, also different time series models (AR(1) and ARX) are compared. With the obtained results, it is found that the proposed method based on the AR model with external influences is the best method. Also the use of the Kalman filter with the ARX model has advantages because of the correction step; the filter can adapt new situations without new parameter identification used the regression method. It can be assumed that this effect will increase with a wider time horizon of the data deployed in the forecasting process. The proposed approach thus provides an alternative and efficient tool for forecasting water demand.

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